GraphWiseLearn: Personalized Learning through Semantified TEL, Leveraging QA-Enhanced LLM-generated Content

Wolfgang Fahl[1,2][0000−0002−0821−6995]

[1] RWTH Aachen University, Computer Science i5, Aachen, Germany
[2] BITPlan GmbH, Willich, Germany

Abstract. In today's educational landscape, from traditional schools to MOOC platforms, the prevalent model is a one-size-fits-all approach to learning content, often overlooking the unique needs and learning paces of individual students. This gap between the ideal personalized instruction by a team of personal trainers and the practicalities of standardization presents significant challenges, including diminished engagement and understanding. My PhD research proposes a Knowledge Graph-based application of core Technology Enhanced Learning (TEL) components, aiming to bridge this divide with a cost-effective method targeted to individual learning objectives and paths.
The core elements of the approach are structured around five key components: Knowledge Graphs (KGs), Large Language Models (LLMs), Flashcards, Visualization of Dynamic Competence Maps (DCMs), and a Quality Assurance (QA) review and feedback workflow.
The approach will collect empirical data on students needs and misconceptions which allow to apply learning analytics for continuous improvement of the learning material.
We hypothesize that this approach will provide a viable method for digitization and entering into a quality improvement cycle based on the rating results, offering a concrete solution for the transition from traditional learning materials.

Keywords: Technology Enhanced Learning · Knowledge Graphs · Large Language Models · Dynamic Competence Map

1 Introduction

The landscape of education and learning methodologies is undergoing a transformative shift with the integration of technological solutions. Traditional educational models often implement a standardized approach to learning, delivering the same material in a uniform manner to all students. This generalized strategy, while logistically straightforward, fails to accommodate the diverse and nuanced needs of individual learners. It overlooks the unique learning styles, pace, and backgrounds of students, resulting in a learning experience that may not fully harness each student's potential. Shemshack's comprehensive analysis of personalized learning components [15] shows the general potential of such approaches as they may be found in current scientific literature.

In response to these challenges, our research introduces a novel combination of KG and TEL approaches designed to provide a personalized learning experience by tailoring educational content to individual needs.

Five key components are applied: Knowledge Graphs (KGs), Large Language Models (LLMs), Flashcards, Visualization of Dynamic Competence Maps (DCMs), and a Quality Assurance (QA) review and feedback workflow.

At the heart of this framework is a knowledge graph capturing the learning content. A semi-automatic semantification of learning content from various sources—such as PowerPoint slides, PDFs, and plain texts—is employed to populate the knowledge graph, emphasizing alignment with specific learning goals. The complexity of this KG, with a hierarchical representation of a Competence Tree as the leading structure, is mitigated by visualizing the learning progress using Dynamic Competence Maps (DCMs). Individual learning paths aligned with the learning goals are provided by using Language Model-generated (LLM) flashcards and assessments. The assessments enable decisions about the most effective learning content to be offered next. This combination not only enables a personalized learning journey but also ensures that the content is dynamically aligned with each learner's progress and understanding. Since LLM-generated content may still be of poor quality at the current state of the art, a quality assurance workflow is applied, involving cost-effective human interaction through a star-rating approach.

The subsequent sections of this paper will outline the architecture of our proposed framework, the methodology employed to curate and structure educational content into a knowledge graph, and the interactive learning platform that leverages Large Language Models (LLMs) for content generation and assessment-feedback cycles. We will explore the effectiveness of this approach through empirical research, aiming to validate our hypothesis that such a personalized, technology-enhanced learning model provides a viable path from traditional learning approaches to a continuous improvement, TEL-based approach while maintaining or improving outcomes, motivation, satisfaction, and overall learning experience.

2 State of the Art

Technology Enhanced Learning: Justin Reich argues in *Failure to Disrupt* [13] that despite the potential of Technology Enhanced Learning tools[3] such as Massive Online Courses (MOOCs) [14], Learning Management Systems (LMS), Adaptive Learning Technologies, Flipped Classrooms, Educational Games and Gamification, Personalized Learning, Online Peer Tutoring, Collaboration Platforms, Automated Scoring and Feedback Tools these technologies alone cannot significantly improve learning outcomes without addressing deeper systemic

[3] https://cr.bitplan.com/index.php/TEL_approaches

issues in education. Continuous Improvement (CI) principles, specifically the DMAIC (Define, Measure, Analyze, Improve, Control) methodology, are presented by Carnovale et al. [3] as a necessary approach for the pedagogical assessment of online learning programs, potentially addressing the limitations highlighted by Reich.

Learning Taxonomies and Ontologies: Defining clear learning goals is foundational to all learning activities. Learning taxonomies proposed by Miller, Bloom, and Anderson and Krathwohl [11,2,1] provide a structured approach to this. Heist et al. [7] introduce a competency ontology aimed at competency management in rapidly evolving fields such as AI, utilizing knowledge graphs for better integration and scalability.

Flashcard Learning and Zettelkasten: Heinrich Schliemann's method evolved into the flashcard technique, further refined by Sebastian Leitner [9] to employ spaced repetition for efficient memorization. Research by Malashenko et al. [10] validates the effectiveness of digital flashcard systems in improving learning effectiveness.

Personalized Learning Paths: The work of Durand, Belacel, and LaPlante [4] on using graph theory to recommend personalized learning paths addresses the sequential and dependent nature of learning materials. Learning styles based on Experience Learning Theory (ELT) are explored by Bo Heffler [6], highlighting the importance of aligning educational approaches to individual learning preferences.

Personal Knowledge Graph E. Ilkou discusses the development and evaluation of Personal Knowledge Graphs (PKGs) in e-learning platforms [8], demonstrating their potential to enhance learning by linking user activities to broader knowledge graphs for personalized content delivery. It outlines future research directions, including privacy enhancements and integration with semantic technologies to provide personalized educational recommendations and more interactive learning experiences.

Yang's PKG (Personal Knowledge Graph)[17] approach for recommendations is not considered state-of-the-art anymore with the rise of large language models (LLMs) because it requires extensive collection and manual structuring of entities and relationships specific to individual users, a process that is resource-intensive and less scalable. In contrast, LLMs can dynamically generate personalized recommendations by understanding and processing vast amounts of data across contexts, providing more flexibility and efficiency without the need for pre-constructed user-specific graphs.

Dynamic Competence Maps: The term "Kompetenzbilanz" (Skills/Competency balance) has been introduced in 2003 by Erler [5]. Triebel wrote his PhD thesis on "Kompetenzbilanzierung" [16]. According to Preißer and Völzke [12] competency assessment in adult education inconsistently applies definitions, Methods, varying from descriptions and observations to measurements, may occur in real-time ("in actu") or retrospectively, and range from standardized to qualitative, often based on self or external evaluations, prioritizing usability, practicability and cost over precise validity. Dynamic Competence Maps capture individual competency balance results over time and allow to visualize these as a skills wheels or radar charts.

LLM Generated Learning Material: Yue Yin's thesis [18] demonstrates the capability of LLMs like ChatGPT4 to create individualized learning content, despite limitations in semantic richness and accuracy, marking a step forward in the application of AI in education.

3 Problem Statement and Contributions

Our research is centered on addressing the lack of personalization and adaptability in traditional learning environments. The one-size-fits-all approach, prevalent in most educational systems, fails to consider individual differences in learning styles, pace, and background knowledge, leading to suboptimal educational outcomes.

Technology Enhanced Learning (TEL) approaches are not living up to their promises yet. A viable approach for the transition from traditional learning approaches to digitization, continuous improvement and personalized learning is needed.

3.1 Research Hypothesis

We hypothesize that the integration of five core elements will enhance the learning process in a cost/benefit effective way.

These elements include:

1. Knowledge Graphs,
2. Visualizations of Dynamic Competence Maps (DCMs) as tools for progress tracking,
3. Language Model-generated flashcards and assessments,
4. Flashcard-style learning, and
5. QA review and feedback implemented through a star rating system.

3.2 Research Questions

The following research questions guide our investigation:

- **RQ1:** What changes in the cost/benefit ratio occur with the introduction of LLM-generated content that is quality-enhanced through a cost/benefit optimizing workflow, as outlined in Section 3.3?
- **RQ2:** How does providing individualized and adaptive learning paths based on such assessments, as proposed, affect the learning experience of individual learners?
- **RQ3:** What insights and quality improvement approaches are possible based on the empirical data that is gathered using this approach?

3.3 Contributions

The novel idea of our research is to combine well-known TEL approaches, such as Personalized Learning, Learning Management Systems, and Adaptive Learning Technologies, with LLMs in a cost/benefit and quality-optimizing way. Our research aims to make the following contributions to the fields of the Semantic Web and technology-enhanced learning:

Semi-automated Semantification of Learning Content The RWTH Aachen University i5 chair for Database and Information Systems (DBIS) Lecture Semantic Mediawiki[4] demonstrates the principle of taking input from PowerPoint and enriching it with metadata that enables cross-linking learning content. This Semantic Mediawiki contains the learning content of the lecture as a knowledge graph. The semantified form of the lecture has been curated from PowerPoint presentations, Moodle content, and a spreadsheet that provides metadata such as links between the items:

- 8 Presentation Pages derived from the original PowerPoint material files
- 11 Chapters derived from the 11 lecture sessions
- 550 Slide pages derived from the PowerPoint slides
- 95 Learning Goal pages
- 169 Keyword pages
- 26 Publication pages

The core entities are represented by the Semantic Mediawiki Concepts Presentation, Chapter, Slide, Learning Goal, Keyword, and Publication, which capture the metadata attributes and relations of the learning content and are computer-readable and queryable.

Dynamic Competence Map Visualization The visualization of learning progress is often achieved using Skills Wheels[5] or Radar Charts. The Dynamic Competence Maps (DCM) Visualization as depicted in Figure 1 has been implemented as part of the BMBF-funded TrainSpot2 project (Grant 16INB2062B) in the dcm GitHub[6] open-source project to supply both visualizations in SVG format based on computer-readable Syllabus and Learner Achievement inputs. This visualization is used for progress feedback of individual learners and for maintaining a flashcard-style trace of learning content items already visited. The frequency of repetition is initially adjusted to the learners' self-assessment and, with each assessment, adapted to their performance.

LLM-generated personalized learning and assessment content A first step is collecting learners' individual background details with a few interview questions about their current role, educational background, prior knowledge, expectations,

[4] http://dbis-vl.wikidata.dbis.rwth-aachen.de/index.php/Main_Page
[5] https://wiki.bitplan.com/index.php/Skills_Wheel
[6] https://github.com/WolfgangFahl/dcm

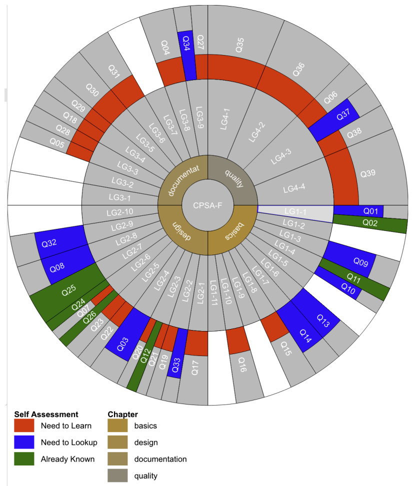

Fig. 1. Dynamic Competence Map Visualization

and aspired achievements. Combining this personal background information with the learning material knowledge graph allows supplying the learner with individualized content generated by an LLM based on this input. A small ChatGPT-4 experiment[7] showcases the potential.

Cost/benefit optimized content Quality assessment workflow The diagram in Figure 2 illustrates the workflow of the star rating system with peer review used for assuring and improving the quality of the learning content. The roles LLM, Learner, Assistant and Teacher are assigned different rating rights based on the assumed cost involved with each role.

Empirical Data for Learning Analytics The interaction of students with the TEL system will be traced to supply data for learning analytics, focusing on students' individual needs and misconceptions. This will enable continuous improvement (CI)/define-measure-analyze-improve-control (DMAIC) quality improvement cycles to be applied to the learning content.

4 Research Methodology and Approach

The first step involves semantifying the teaching content. For this purpose, the Python-based open-source project pySemanticSlides[8] has been developed for PowerPoint presentations. This tool enables the extraction of text and graphics from PowerPoint slides and supports annotations that provide additional

[7] https://cr.bitplan.com/index.php/Workdocumentation_2024-02-02
[8] https://github.com/WolfgangFahl/pySemanticSlides

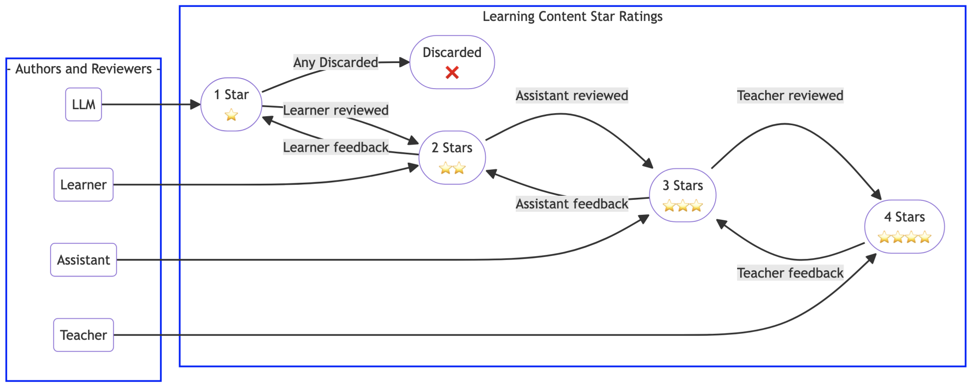

Fig. 2. Star Rating System with Peer Review Workflow (UML State diagram)

metadata. The extracted content is then transformed into Semantic MediaWiki pages, utilizing Semantic MediaWiki's Concept and Property elements to form a Knowledge Graph. The Wiki is intentionally read-only and is not open for direct student use. Instead, frontends are applied.

One frontend collects personal background data from learners, such as their role, previous education, current environment, prior knowledge, expectations, and interests. It then provides a visual representation of a Dynamic Competence Map (DCM), assessing the learner's current knowledge level. Leveraging this input, an LLM-based interactive learning platform enhances the richly linked wiki content. Using the "Zettelkasten" method, the LLM generates individualized quiz cards, exam questions, and exercises based on standard material, tailored to the learner's background and current knowledge as tracked by the DCM visualization.

A second frontend delivers the actual learning experience by monitoring navigation through content links and offering self-assessments and repetition based on the learner's path.

Learners are actively involved in the quality improvement of the material—they will not only passively answer questions but also be posed with the task of "Are you capable of asking a good question on this topic?". By creating their own content and rating the content of LLMs and peers, a larger, more individualized, and higher-quality learning content base is created.

5 Evaluation/Evaluation Plan

Engagement Evaluation: We intend to measure learner engagement with the platform. Metrics will include time spent on the platform, interaction rates with the learning materials, and progression through the Dynamic Competence Maps in comparison with the self-assessment results. A focus will be on identifying misconceptions and clustering groups of learners with similar individual needs.

Learning Outcomes: Although we acknowledge the challenges highlighted by Reich in measuring significant objective differences between traditional methods and technology-enhanced learning solutions, we intend to interview learners to gather insights into how they perceive the impact of our framework on their motivation, satisfaction, and overall learning experience.

The systems under development shall be scientifically evaluated in the RWTH Aachen i5 course database and information systems, with volunteers recruited from some 600 students per semester. As the chief trainer of BITPlan GmbH and initiator of the International Software Architecture Qualification Board (iSAQB) e.V.[9], the author intends to propose the application of the DCM feedback mechanism to that association. The iSAQB e.V. is responsible for the syllabus "Certified Professional for Software Architecture (CPSA-F)." There is a strict separation of responsibility in the certification workflow between syllabus creation, training, and certification, which are done by independent organizations - therefore, the members' meeting needs to decide on this move. Participants of CPSA-F trainings may be offered access to the system and interviewed, depending on the acceptance of the proposal.

6 Results

At this stage, only preliminary results are available, which demonstrate the technical feasibility of the GraphWiseLearn approach. For example, the wiki content has been cross-checked to ensure the integrity of the provided metadata and content aligns with the original learning material. The Cross-check results[10] show 20 deviations out of over 2000 checks that have been performed, indicating a much higher consistency than would have been the case with manual curation.

The KG based approach for the learning material has been proven to be effective for some 750 participants of software architecture trainings in the past. The main advantage being the straightforward connection between learning goals, learning content, and self-assessment elements such as quiz cards.

In one of the author's software architecture trainings, ten participants used a self-assessment tool that is based on the DCM visualization. During the training, the focus on learning goals with statistical relevance was well received.

7 Conclusions/Lessons Learned

In Summer Semester 2022 the semantified DBIS Lecture has been offered as a learning tool for students for the first time. There has been no scientific evaluation during that semester. Since their was no frontend the individual interactions of the students could not be traced.

[9] https://www.isaqb.org
[10] http://dbis-vl.wikidata.dbis.rwth-aachen.de/index.php/List_of_Checks

Traditionally, teaching resources, including slides, videos, exercises, and exams, constitute a stable fund of material. While the foundational content remains relatively constant, exercises and exams require regular updates to stay relevant for each new lecture iteration.

Our approach offers a viable way to shift towards knowledge graph-based digitization, thereby enabling the application of technology-enhanced learning.

This transition facilitates the dynamic evolution of educational content by leveraging empirical data on student needs and misconceptions, which was previously unattainable.

Integrating content and assessments generated by Large Language Models (LLMs) with crowd-sourced human review cycles offers a promising strategy. This method establishes a continuous cycle of improvement for training materials, enabling the iterative refinement of teaching content based on actionable insights gained from learner interactions. This route promises a cost-effective way of personalizing teaching with a much larger fund of material targeted at the needs and misconceptions of learners.

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